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Procedia Computer Science 17 (2013) 298 – 305

Procedia
Computer Science

Information Technology and Quantitative Management (ITQM2013)

Modeling Maintenance Effect with failure-counting

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Abstract

The assessment and modeling of the maintenance effect is an active research topic. In this paper, we proposed a failure-counting-based maintenance effect assessment model (abbreviated as FCME). Specifically speaking, this model assumes that a system failure process during a preventive maintenance interval can be described as an independent failure path. The initial independent failure path can be denoted as the inherent failure path. Furthermore, the current failure can be presented as the sum of the last failure path and the increment that is proportional to the difference between the inherent and last failure path. This proportion is used to represent the preventive maintenance effect. Moreover, the failure path is modeled by a random failure point process model. In order to illustrate the effectiveness of the proposed method, a numerical example is presented based on the data referenced from previous literatures. Then the model is used to assess the preventive maintenance effect of a bus fleet with the real world operating data.

Selection and peer-review under responsibility of the organizers of the 2013 International Conference on Information Technology and Quantitative Management

Keywords: Maintenance effect, preventive maintenance, failure-counting, repairable system, multi-type preventive maintenance, bus fleet;

1. Introduction

A mass of complex engineering systems not only are repairable but also are performed a series of maintenance systems. Since the components of many systems degenerate with time and result in system failure eventually, preventive maintenance (PM for short) is used to slow the degradation process and extend the system life (e.g., lubrication of mechanical systems). So comparing to the non-repairable system, the following characters should be considered when carry out the reliability analysis and modeling:

(1) Inherent reliability, operating conditions and maintenance system can affect system operating reliability.

(2) Repairable system can suffer many times of failure. And the successive times between failures is not independent and identically distributed. Therefore, an important basic model is failure point process. One of the

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Selection and peer-review under responsibility of the organizers of the 2013 International Conference on Information Technology and Quantitative Management
doi:10.1016/j.procs.2013.05.039

main streams of development of the analysis of failure point process is Non-homogeneous Poisson Process (NHPP for short). Two well-known models of the NHPP are power-law model (PLM for short) and log-linear model (LLM for short).

Much attention has been paid to modeling the maintenance effect. The age reduction models use an concept of virtual age, denoted as τ , to describe the reduction of age in failure intensity model. For example, the failure intensity at age t will be reduced to the situation of $t-\tau$ after a maintenance activity. The earliest age reduction model developed by Malik [1], assumed that the decrement of age was proportional to the latest operating time. More age reduction models can be found in references [2-5]. Furthermore, another concept of failure intensity reduction is used. Nagakawa [5] also assumed PM activities can first bring the failure intensity to zero, and the failure intensity increases more quickly than it did in the previous PM interval. Chan and Shaw [6] presented an arithmetic failure intensity reduction model. This model assumes that the failure intensity will decrease a certain value after a PM activity. The "certain value" is randomized between 0 and the previous level. Some other failure intensity reduction models can also be found in a number of papers [7-9]. Moreover, geometric process can also be used in modeling failure intensity reduction [10]. While, Lin et al. [11] presented a hybrid model through combining the models proposed by Nagakawa. Finkelstein [10] proposed a scale-model of general maintenance. This model assumed that the system life after a maintenance activity is proportional to the life of a new system. The proportion is randomized between 0 and 1. Biswas and Sarkar [12] developed an arithmetic process model, which assumed that the system life can only be harvested of the new system life after the PM. Furthermore, there are many papers carried out the maintenance optimization by considering maintenance effect [13-24]. More details can be found in these papers.

However, these models have strong pertinence. For example, the imperfect maintenance model is to deal with the situation of WNBO, the Renewal Process model (RP) is to resolve the situation of AGAN. Therefore, this paper will propose a flexible maintenance effect assessment model, which is a failure-counting-based maintenance effect assessment model (abbreviated as FCME). Specifically, we assume that a system failure process during a PM intervals can be described as an independent failure path. The initial independent failure path denoted as the inherent failure path. Furthermore, the current failure can be presented as the sum of the last failure path and the increment that is proportional to the difference between the inherent and last failure path. This proportion represents the relative PM effect. Moreover, the failure path is modeled by a random failure point process model. The modeling process is conducted. In order to illustrate the effectiveness of the proposed method, a numerical example is presented. The data is referenced from previous literature. Then the model is used to assess the PM effect of a bus fleet with the real world operating data.

The remainder of this paper is organized as follows. Section 2 presents the proposed modeling method. A numerical example is carried out to illustrate the effectiveness of the proposed method in Section 3. The practical application example in bus fleet is presented in Section 4. Finally, this paper is discussed and concluded in Section 5.

2. FCME model

Suppose a complex repairable system is subjected a PM. During the time between PM, there also are some operational failure happening. Upon an operational failure, the system will be restored to the work state as soon as possible. We also assume that the repair and PM time can be ignored. For a given calendar time t_i, the cumulative operating failure can be obtained. Throughout the failure-repair process, we can obtain the following operating records:

$$\left|\begin{array}{llllll} & PM & PM & PM & PM & PM \\ 1t & 1 & 2 & \cdots & 1 & \cdots \\ 2t & 1 & 2 & \cdots & 4 & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots \\ (i\text{-}1)t & 17 & 18 & \cdots & 27 & \cdots \\ it & 18 & 20 & \cdots & null & \cdots \end{array}\right| \Rightarrow \left|\begin{array}{llllll} & PM & PM & PM & PM & PM \\ 1 & N(t_{0,1}) & N(t_{1,1}) & \cdots & N(t_{j,1}) & \cdots \\ 2 & N(t_{0,2}) & N(t_{1,2}) & \cdots & N(t_{j,2}) & \cdots \\ 3 & N(t_{0,3}) & N(t_{1,3}) & \ddots & N(t_{j,3}) & \ddots \\ \vdots & \vdots & \vdots & \cdots & \vdots & \cdots \\ i & N(t_{0,i}) & N(t_{1,i}) & \cdots & N(t_{j,i}) & \cdots \end{array}\right|, \tag{1}$$

where $N(t_{j,i})$ denotes the cumulative failure number at the $i\text{-}th$ time units during the $j\text{-}th$ PM. In the operating records (1), some details can be explained. On the one hand, the records of cumulative failure number may be non-homogeneous. For example, a type-II PM is performed ahead of the calendar time it . On the other hand, the time between PM is non-homogeneous too. Generally speaking, the PM may not be performed on the initial planning time even a periodic PM is. Finally, maybe p similar systems need to be analyzed. However, the observation time points are different. In this paper, these problems can be resolved by the method of interpolation or extrapolation. For example, a simple linear interpolation relation can be described as:

$$N(t_{j,i}) = N(t_{j,i-1}) + (t_{j,i} - t_{j,i-1})\frac{N(t_{j,i+1}) - N(t_{j,i-1})}{t_{j,i+1} - t_{j,i-1}}, t_{j,i-1} < t_{j,i} < t_{j,i+1}. \tag{2}$$

We call this step as PM time homogenization.

2.1. Model idea

We take the single-type PM as an example to state the idea of the proposed FCAM model, which can be described by:

$$N(t_{j,i}) = N(t_{j-1,i}) + \sigma_j X(t_{j,i}), X(t_{j,i}) = M(t_{j,i}) - N(t_{j-1,i}), \tag{3}$$

In the proposed model, we assume that:

(1) an inherent failure path can be determined by the initial failure process. The inherent cumulative failure number at the $i\text{-}th$ time units during the $j\text{-}th$ PM interval is denoted as $M(t_{j,i})$;

(2) the observed cumulative failure number at the $i\text{-}th$ time units during the $j\text{-}th$ PM interval is $N(t_{j,i})$.

(3) σ_j is the maintenance effect of the $j\text{-}th$ PM. More accurately, σ_j is a relative maintenance effect, owing to the inherent failure path may not be the failure path of a new system. It may be determined by the intermediate operating stage;

(4) $X(t_{j,i})$ is the increment between the inherent cumulative failure number of the current PM interval and the observed failure number of the last PM interval. It represents the increment of cumulative failure number if there is not a PM activity performed. But the increment will be proportional to $X(t_{j,i})$ with a proportion σ_j due to the PM activity;

(5) and the cumulative failure number is an important character of CM effect. If the CM effect is very bad, system failure will happen more frequent than before. Moreover, the failure path can be described by a random failure point process model.

2.2. FCME model

If there exists only a single-type PM, equation (3) can be derived as follows:

$$\left\{\begin{array}{ll} j=1 & N\left(t_{1,i}\right)=N\left(t_{0,i}\right)+\sigma_1 X\left(t_{1,i}\right) \\ j=2 & N\left(t_{2,i}\right)=N\left(t_{1,i}\right)+\sigma_2 X\left(t_{2,i}\right)=N\left(t_{0,i}\right)+\sigma_1 X\left(t_{1,i}\right)+\sigma_2 X\left(t_{2,i}\right) \\ \cdots & \cdots \\ j=n & N\left(t_{n,i}\right)=N\left(t_{n-1,i}\right)+\sigma_n X\left(t_{n,i}\right)=N\left(t_{n,i}\right)+\sigma_1 X\left(t_{n,i}\right)+\ldots+\sigma_n X\left(t_{n,i}\right)=N\left(t_{n,i}\right)+\sum_{j=1}^{n}\sigma_j X\left(t_{j,i}\right) \end{array}\right\}, \quad (4)$$

where $X\left(t_{j,i}\right)=M\left(t_{j,i}\right)-N\left(t_{j-1,i}\right)$, we can further obtain:

$$N\left(t_{n,i}\right)=N\left(t_{0,i}\right)+\sum_{j=1}^{n}\sigma_j M\left(t_{j,i}\right)-\sum_{j=1}^{n}\sigma_j N\left(t_{j-1,i}\right). \quad (5)$$

Assume the PM times are $T_j, j=1,2,...,n$, while the PM is periodic PM if $T_1=T_2-T_1=T_3-T_2-T_1=T_n-\cdots-T_2-T_1$. Even the PM times are different from each other, so we also can use the method of interpolation or extrapolation to obtain humongous data. Moreover, the PM activities are same if the maintenance effects, $\sigma_j, j=1,2,...,n$, are equal to each other $\sigma_1=\sigma_2=\cdots=\sigma_n$. Otherwise, it is reasonable to assume that the maintenance effects are following a certain function, for example the gamma or normal distribution. Then equation (5) can be represented as:

$$N\left(t_{j,i}\right)=N\left(t_{0,i}\right)+\sum_{q=1}\sigma_q \operatorname{Ind}\left(T_j\le t_j<T_{j+1}\right)M\left(t_{j,i}\right)-\sum_{q=1}\sigma_q \operatorname{Ind}\left(T_j\le t_j<T_{j+1}\right)N\left(t_{j-1,i}\right). \quad (6)$$

where ρ_j is arbitrary. It means that the maintenance activity can resort the system to the state as good as new if $\rho_j=0$, as bad as old when $\rho_j=1$, Better than old but worse than new when $\rho_j\in(0,1)$, badly the system will harvest worse failure intensity than before if $\rho_j>1$, and if $\rho_j<0$, the system will be better than new. It means the system is at the state of reliability improvement.

The indicator function is defined as follows:

$$\operatorname{Ind}\left(\phi(\cdot)\right)=\begin{cases}1 & \textit{if } \phi(\cdot) \textit{ is true}\\ 0 & \textit{otherwise}\end{cases}. \quad (7)$$

Afterwards, the model parameters/relative maintenance effects can be estimated by minimizing the sum of squared errors (SSE for short), which is expressed as:

$$SSE=\sum_i\sum_j\left[O\left(t_{j,i}\right)-N\left(t_{j,i}\right)\right]^2, \quad (8)$$

where $O(\cdot)$ is the observed cumulative failure number.

Furthermore, the well-known power-law model will be used to model the failure process in this paper. The PL model with parameter is given by:

$$M\left(t_j\right)=\left(\frac{t_j+\gamma_j}{\alpha_j}\right)^{\beta_j}, \quad (9)$$

The model parameters can also be estimated by minimizing the SSE:

$$SSE=\sum_j\left[O\left(t_j\right)-M\left(t_j\right)\right]^2, \quad (10)$$

where $O(\cdot)$ is the observed cumulative failure number.

3. Numerical examples

Zhao et al. [25] provides an analysis of a set of data on time between failures on a double-boxed beam gantry crane with 10t rated lifting capacity. The original data given by Zhao is time between failures of six times PM. In this paper, we transform the original data into failure-counting data, as shown in Table 1 (a). Then the proposed FCME model is used to model the maintenance effects of the sit times PM. The model results are displayed in the last six rows of Table 1 (a). We obtain the average maintenance effect is 0.1284. The fitted effect is shown in Fig. 1, where we can see that there is almost no difference between the observed path and the fitted path. So we can conclude that the fitted effect is very well.

Table 1 Data and analysis results

a. Data of Crane from [25] and analysis results

	1st	2nd	3rd	4th	5th	6th
90	1	0	0	1	1	1
180	1	2	2	2	1	2
270	1	2	2	3	2	4
360	3	2	3	4	3	4
450	3	4	4	5	4	5
540	5	5	4	5	5	6
630	5	6	5	6	6	7
720	5	6	7	7	7	8
810	6	8	7	8	8	9
900	8	9	8	9	9	11
990	8	10	9	11	11	13
1080	9	10	10	12	12	15
1170	10	12	11	13	13	17
1260	11	13	13	14	16	19
1350	12	14	14	15	17	22
1440	13	14	16	18	19	24
1530	14	15	18	19	21	25
1620	15	16	19	21	23	27
1710	16	17	20	23	25	29
1800	17	18	21	24	27	30
1890	18	20	22	26	30	
1980	19	21	24	28		
2070	20	23	26	30		
2160	21	24	28			
2250	23	26	30			
2340	25	27				
2430	27	29				
2520	28	30				
2610	29					
2700	30					
MTBT	90	84	75	69	63	60
α	319.97	229.06	286.77	405.54	369.23	226.82
β	1.53	1.38	1.58	1.87	1.91	1.60
γ	244.36	153.33	181.98	437.27	287.40	159.00
ME	—	0.12	0.17	0.13	0.12	0.10
ME'	0.1205(ME Average: 0.1284)					

b. Failure data of the bus fleet and analysis results

	1st	2nd	3rd	4th	5th	6th
1	0.0003	0.0057	0.0107	0.0158	0.0211	0.0263
2	0.0015	0.0116	0.0216	0.0319	0.0423	0.0529
3	0.0028	0.0178	0.0328	0.0481	0.0638	0.0796
4	0.0043	0.0241	0.0441	0.0646	0.0854	0.1066
5	0.0060	0.0305	0.0556	0.0812	0.1073	0.1337
6	0.0078	0.0372	0.0673	0.0981	0.1294	0.1611
7	0.0099	0.0441	0.0792	0.1151	0.1516	0.1886
8	0.0121	0.0511	0.0913	0.1324	0.1741	0.2164
9	0.0145	0.0584	0.1036	0.1498	0.1968	0.2444
10	0.0170	0.0658	0.1160	0.1674	0.2197	0.2725
11	0.0198	0.0735	0.1287	0.1853	0.2427	0.3009
12	0.0227	0.0813	0.1416	0.2033	0.2660	0.3295
13	0.0259	0.0893	0.1547	0.2216	0.2895	0.3583
14	0.0292	0.0975	0.1680	0.2400	0.3132	0.3873
15	0.0327	0.1059	0.1814	0.2586	0.3371	0.4165
16	0.0363	0.1145	0.1951	0.2775	0.3612	0.4459
17	0.0402	0.1233	0.2090	0.2965	0.3855	0.4755
18	0.0442	0.1323	0.2230	0.3158	0.4100	0.5053
19	0.0485	0.1414	0.2373	0.3352	0.4347	0.5353
20	0.0529	0.1508	0.2517	0.3549	0.4596	0.5655
21	0.0575	0.1604	0.2664	0.3747	0.4847	0.5960
22	0.0623	0.1701	0.2813	0.3948	0.5100	0.6266
23	0.0673	0.1801	0.2963	0.4150	0.5355	0.6574
24	0.0724	0.1902	0.3116	0.4355	0.5612	0.6885
25	0.0778	0.2005	0.3270	0.4561	0.5872	0.7197
26	0.0833	0.2111	0.3427	0.4770	0.6133	0.7512
α	2.38					
β	30.10					
γ	1.91					
ME	—	0.2772	0.1105	0.3094	-0.2638	0.2588

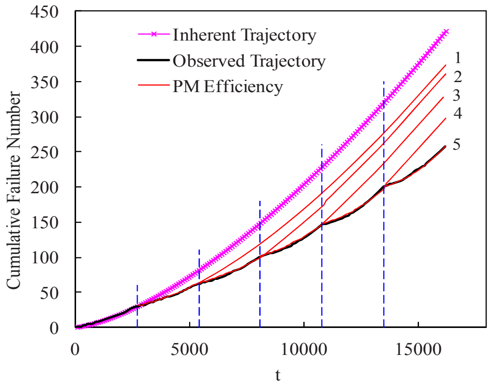

Fig. 1. Fitted results of two numerical examples

4. Application in Bus fleet Maintenance

4.1. Data and background

A certain bus company runs 48 bus routes. A monotypic fleet of 22 buses started operating in a route on August 24, 2005. In order to maintain the operational reliability and safety, the bus company performs a complete set of maintenance system. The bus is usually subjected to time-based PM. In addition, the government stipulates that the bus should not be retired during eight years only the case that the bus condition complies with the relevant requirements. Otherwise, the bus must be retired at no more than eight years.

Upon an operational failure, the bus is restored by a corrective repair, which can be deemed as a minimal repair though certain opportunistic maintenance actions may be combined. Management information system records the failure information, such as failure time, repair cost and downtime.

To illustrate the effectiveness of the proposed method, we collected a fleet of 22 buses (with the same model) operational data from September 1, 2006 to December 31, 2009, including failure time, and PM times. The fleet has been subjected 9 times PM with an average interval of 153 days.

For the sake of confidentiality, the data presented in this paper, displayed as in Table 1 (b), has been rescaled and the unit is omitted. But this does not influence the analysis and conclusions.

4.2. PM effect assessment

In the analysis process, we model the failure path of the first PM interval to obtain the inherent failure path. Then use the FCME model to modeling the remainder PM effects, through the modeling process stated in section 3.4. The fitted result is shown in Fig. 2 (a) and the analysis results are displayed in Table 1 (b).

We can see that the fitted effect by our model is very well. The observed failure path is very close to the fitted failure path. In addition, there is a bad maintenance, the 5^{th} type-II PM, whose maintenance effect is -0.2638. It also illustrates the apply areas of our method: five situations of maintenance effects can all be covered. Although there are many times of type-I PM, but the maintenance content is focuses on cleaning, lubrication and fastening, the effect is so little that we have not considered the maintenance effect of them.

Furthermore, we carry out the cost analysis of the type-II PM based on the cost data. The relationship between type-II PM cost and maintenance effect are shown in Fig. 2 (b). We can see that the higher cost will be if better maintenance effect wanted. But more ironically, worse maintenance effect want to harvest, higher maintenance cost will be spent.

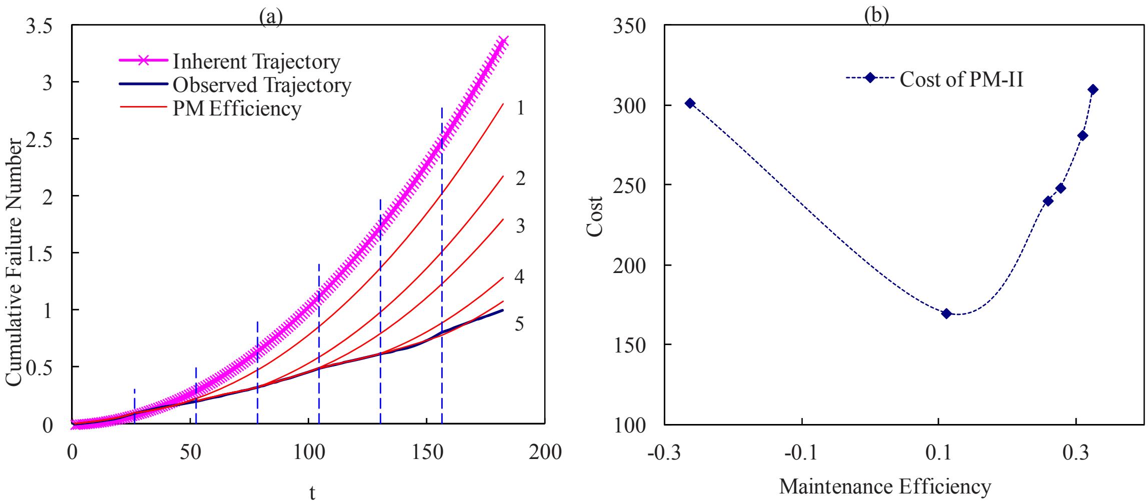

Fig. 2. (a) Fitted results of bus fleet’s maintenance effect; (b) cost analysis

5. Conclusions

In this paper, we proposed a failure-counting base maintenance effect assessment model, abbreviated as FCME model. And the modeling processes were presented. From the numerical example conducted based on the data referenced from previous literatures, we concluded that the proposed model is effective. The model was also used to assess the PM effect of a bus fleet with the real world operating data. The result shows that the fitting is very well. Furthermore, the relationship between maintenance effect and maintenance cost were analyzed. We found that the higher cost spent, the better maintenance effect can be obtained. But more ironically, worse maintenance effect want to harvest, higher maintenance cost will be spent. Thus, the proposed model is very flexible, which is appropriate for all situations of maintenance effect. Meanwhile, our model takes into account both CM and PM effect.

Based on the present work, we will carry out many other relative works in our future work. On the one hand, the proposed model is based on the failure history. After a PM activity, how to assess the maintenance effect if there is no enough failure observed. In the case study, we analyzed the relationship between maintenance effect and cost. Because of the unimodality of the relationship, the cost index cannot identify the maintenance effect independently. So, more auxiliary information should be mining. On the other hand, new PM plans should be generated based on the proposed PM effect assessment method. Maintenance optimization is a complex mathematics problem. In addition, the system lifetime is finite, thus the preventive maintenance decision making under the finite planning horizon is a meaningful study. In the existing literatures, since the maintenance effect is seldom considered in period or sequence PM optimization, the period or sequence PM optimization method should be developed considering the maintenance effect. Finally, the failure seriousness is different to each other. So maintenance effect assessment method based on the failure seriousness can also be worth to study. However, the closer to actual more complex mathematics need to face, and more complex stochastic optimization techniques are needed.

Acknowledgements

This research has been partially supported by grants from the National Natural Science Foundation of China (#71222108) and the Fundamental Research Funds for the Central Universities (#ZYGX2012YB035).

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